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The Role of Emotional Regulation in Anxiety and Depression Symptom Interplay and Expression among Adolescent Females

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Abstract

Depression and anxiety are highly comorbid constructs. However little is known about the mechanisms that underpin this comorbidity/connectivity or the divergence between constructs that seems to occur in adolescence. The current study targeted emotion regulation (ER) as a potential plausible mechanism for explaining how anxiety and depression symptoms in adolescence might begin to connect, perpetuate, and ultimately diverge from one another. Using data from a cross-sectional school-based study, of adolescent females (age 11–18 years; $N = 615$; majority were white (97.7%)), we modelled variation in ER using latent profile analysis. Then, using network analysis (NA), we generated separate depression-anxiety symptom networks for adolescents at varying levels of ER. Three latent classes of ER were identified (low ER 15%, intermediate ER 34%, high ER 51%). The results of the network comparison test found no significant differences in global strength between the 'low ER' and the 'intermediate ER' ability network. This study is among the first to attempt to model change in depression-anxiety symptom connectivity in adolescence in relation to a common contextual/risk factor. The current study therefore offers a unique contribution to the examination of the role of transdiagnostic factors in the study of adolescent depression and anxiety from a network perspective, and provides a promising framework for the study of ER among anxiety and depression symptomatology in adolescence.

Keywords Adolescent psychopathology · Emotional regulation · Depression · Anxiety · Comorbidity · Network analysis

A wealth of empirical research evidence has established that a high degree of co-morbidity exists between anxiety and depressive disorders in adolescence, with prevalence rates of comorbidity ranging from 20 to 50% among clinical samples (González-Tejera et al., 2005; Løvaas et al., 2018; Ollendick, Shortt & Sander, 2005; Schleider, Vélez, Krause & Gillham, 2014). Additionally, recent research has also demonstrated the presence of co-occurring symptoms of depression and anxiety in subclinical forms among adolescents within the general population (van Lang, Ferdinand, Matthew, Ormel & Verhulst, 2006; Wadsworth, Hudziak, Heath & Achenbach, 2001). While these sub clinical symptoms of depression and anxiety do not meet diagnostic thresholds, they have been found to contribute to high levels of distress and impairment for those who experience them and greatly increase the risk of future psychopathology and suicidality (Balazs et al., 2013; González-Tejera et al., 2005; Jinnin et al., 2017; Løvaas et al., 2018). However, despite the clear clinical relevance of subthreshold symptoms of anxiety and depression in adolescence, it remains a largely understudied area (Jinnin et al., 2017). Overall, there is consensus that this comorbid relationship is associated with greater severity of symptomatology, risk of suicide and future psychopathology, than either disorder separately (Garber & Weersing, 2010).

In an attempt to investigate how anxiety and depressive disorders co-occur, network theory and network analysis (NA) offer a novel conceptual framework and statistical technique to understand and explore the underlying connectivity between the symptoms of both constructs (Borsboom, 2017). The network approach conceptualises mental disorders, as a system of networks whereby symptoms within the network interact and reinforce one another (Cramer et al., 2010; Borsboom & Cramer, 2013; Fried et al., 2017; Borsboom, 2017). This approach therefore asserts that what is

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traditionally considered a 'disorder' is in fact groups of symptoms which are strongly associated with one another and have influence over one another; in this way the symptoms themselves constitute the disorder. These symptoms are therefore not simply considered to be passive indicators of an underlying latent construct/disorder, as proposed by the common cause model (Cramer et al., 2010; Borsboom & Cramer, 2013). In relation to the study of co-morbidity, this approach suggests that disorders co-occur due to this complex interplay between symptoms, where the symptom of one disorder triggers the symptom of another disorder, known as 'bridging' symptoms (Fried et al., 2017). Network analysis is now a well-established statistical tool, informed by network theory, which affords the opportunity to empirically study the complexity of co-occurring anxiety and depression symptoms, by allowing us to examine the specific symptom level interactions which may play a key role in driving the common co-occurrence of two disorders (Afzali et al., 2017; Beard et al., 2016).

A number of studies employing network analysis to explore co-occurring anxiety and depression symptomatology using adult, clinical and general population, data have demonstrated that anxiety and depression symptom networks are highly connected (Beard et al., 2016; Cramer et al., 2010). These studies have also however shown that anxiety-based symptoms and depression symptoms generally cluster separately (Beard et al., 2016), and that only a few symptoms create a 'bridge' between constructs. For example, Beard et al. (2016) showed that, among the ten strongest edges (i.e. associations between symptoms) in an anxiety – depression symptom network, only one edge provided a bridge between anxiety and depression symptoms (psychomotor retardation/agitation to restlessness).

Distinct, within-construct, symptom clustering however has not always been demonstrated, particularly in younger populations. Recent studies (McElroy et al., 2018; McElroy & Patalay, 2019), using child/adolescent data have revealed a lack of distinct within-construct clustering, instead finding high levels of interconnectivity between all depression and anxiety symptoms. These findings challenge the view that depression and anxiety constitute two distinct phenomena, at least in childhood and adolescence, and suggest a changing manifestation of depression and anxiety symptomatology over development. At present there is a lack of consensus regarding how anxiety and depression should be conceptualised in childhood and adolescence, with some researchers suggesting anxiety and depression in the younger years may take the form of a unidimensional construct, whereas for older adolescents, anxiety and depression may be better conceptualised as two distinct disorders (McElroy & Patalay, 2019; Rouquette et al., 2018).

Whilst the comorbidity between these constructs, and more specifically the connectivity between the symptoms within each construct is widely acknowledged, little is known about the mechanisms underpinning (i) this comorbidity/connectivity or (ii) the divergence between constructs that seems to emerge in adolescence. One construct/mechanism that may plausibly explain each of these issues is emotion regulation (ER). Empirical evidence to date suggests ER plays an important transdiagnostic role in the onset and maintenance of both depressive and anxiety disorders in adolescence (Aldao et al., 2010; Klemanski et al., 2017; McLaughlin et al., 2011; Schäfer et al., 2017). Adolescence has been recognised as the most crucial developmental stage for affective development (McLaughlin et al., 2011) and empirical evidence has suggested it is the frequent occurrence of intense emotions and heightened stress levels that heightens the risk for developing deficits in ER in this age group (Schäfer et al., 2017). In the extant literature, there is consensus that when an adolescent's ability to regulate their emotions is compromised, their affective development may be delayed, which in turn greatly increases the risk of developing several adverse mental health outcomes, including anxiety and depressive disorders (McLaughlin et al., 2011).

Given the well-established evidence base demonstrating the transdiagnostic quality of ER in adolescence, ER may be a plausible mechanism for explaining the context in which a network of anxiety and depression symptoms might begin to connect, perpetuate, and ultimately diverge. Network theory therefore may provide a useful framework to account for ER's transdiagnostic influence in the development and maintenance of depressive and anxiety disorders.

The Present Study

To our knowledge, few studies have examined the co-occurrence of depression and anxiety based symptoms among adolescents within the general population using network analysis. Moreover, there is a lack of consensus regarding the distinctiveness of depression and anxiety symptoms during adolescence and, overall what is currently understood about the complex interplay by which these symptoms co-occur within one another remains in its infancy.

The current study has two overall aims. First, to use network analysis to examine the general symptom structure of depression and anxiety based symptoms among school age adolescents within the general population and explore the extent to which depression and anxiety are distinct constructs within this sample. Secondly, model and compare networks of depression and anxiety symptoms at varying levels of ER. We hypothesised that, in the context of healthy ER, a network of depression/anxiety symptoms would be sparsely connected, with weak/negative connections between nodes (van Borkulo et al., 2015). Conversely, where ER was poorer/more impaired, we hypothesised that a network would become more strongly connected, and that symptoms would begin to mutually reinforce each other (i.e. more strong/positive connections). At the lowest levels of ER, we hypothesised that the network would be most reflective of what is recognised clinically as depression and anxiety. Using network analysis, we aimed to demonstrate the 'emergence' of anxiety and depression against a backdrop of ER variation.

Method

Participants and Procedure

A cross-sectional survey was conducted with a total of 615 female adolescents recruited from two post-primary schools in Northern Ireland (NI) in 2016–2017. All pupils were between 11 and 18 years of age (mean age = 13.32; SD = 2.02), the majority were white (97.7) and lived with both parents (80.7%). Invitation letters were sent to 8 post-primary schools in NI. Parental information and opt-in consent forms were sent to all parents/guardians of the pupils for both post-primary schools who agreed to participate. Adolescents with parental consent were invited to participate in the study during their pastoral care lesson. The anonymous, self-report survey was computerised using the website Qualtrics. The survey was accessed via Qualtrics at each post-primary school site and took approximately 30 min to complete. Ethical approval was granted by the Ulster University Ethics Committee (REC/16/0007). There were no missing data. The online survey was programmed to highlight to a participant when they missed a question on the survey and directed them to answer all questions before they could proceed to the next section.

Measures

Depression and Anxiety Symptomology

Depression and anxiety symptomology were measured using the Patient Health Questionnaire (PHQ-9; Kroenke et al., 2001) and the Generalised Anxiety Disorder Scale (GAD-7; Spitzer et al., 2006). Both scales are self-report measures of symptom severity in line with DSM-IV criteria and the more recent DSM-5 (Diagnostic and Statistical Manual of Mental Disorders, 4th edition; 5th edition). Items in both scales were scored on a 4-point likert scale, ranging from 0 to 4. The response categories were, *not at all* (0), *several days* (1), *more than half the days* (2) and *nearly every day* (3) and related to the past two weeks. Both the GAD-7 and PHQ-9 have demonstrated excellent internal reliability (Kroenke et al., 2001; Spitzer et al., 2006). In the context of the current study, each scale demonstrated excellent psychometric properties, with an internal consistency of .89 for the PHQ-9 and .91 for the GAD-7. Both scales have been utilised across both clinical and community based adolescent research, from age 11 to 18 years (Burdzovic Andreas & Brunborg, 2017; Mossman et al., 2017; Richardson et al., 2010).

Emotion Regulation

The Difficulties in ER scale- short form (DERS-SF) was used to measure deficit's in ER ability, across six domains (Kaufman et al., 2016). The DERS-SF contains 18 items rated on a 5-point likert scale ranging from *almost never* (0) to *almost always* (5), with higher scores indicating greater ER difficulties. The measure yields a total score as well as scores on six sub-scales which are *'non-acceptance'*, *'difficulties with goal directed behaviour'*, *'impulse control'*, *'lack of emotional awareness'*, *'clarity'* and '*limited access to ER strategies'*. DERS-SF has demonstrated excellent psychometric properties within adolescent samples, with internal consistency for both the DERS-SF total scale and six subscales ranging from .78 to .91 (Kaufman et al., 2016). In the context of the current study, the internal consistency of each of the sub scales was high (average α for the DERS-SF subscales was .82). The DERS-SF has been demonstrated as appropriate for adolescents aged 11–17 years (Kaufman et al., 2016).

Analytic Strategy

This study employed a phased analytic strategy. Phase one involved the estimation of a 'general' network of anxiety and depression symptoms, across the entire sample. This was to show how symptoms from both spectra were connected for all participants regardless of ER 'ability'. To capture variation in ER, latent profile analysis (LPA) was used in phase two to identify distinct groups of adolescents who varied in their ability to understand and regulate their emotions. Finally, in phase three, networks were generated for each ER subgroup identified in phase two, to compare anxiety and depression symptom connectivity at different levels of ER i.e. from low ER to high.

Network Estimation

Networks were estimated, using the statistical program 'R version 3.3.2'. Each network structure was estimated using a Graphical Gaussian Model (GGM). GGM was deemed appropriate due to the continuous nature of the data in the current study. Edges, in the context of GGM can be understood as partial associations, which represent the relationship between two nodes whilst controlling for all other relationships in the network (Epskamp et al., 2018). As GGMs typically estimate a large number of parameters, it is common practice to regularise GGM to avoid the possibility of false positive edges (Epskamp et al., 2018). The network structure in the current study was regularised by running the graphical LASSO (Least Absolute Shrinkage and Selection Operator; Friedman et al., 2008) via the R package qgraph (Epskamp et al., 2012). The graphical LASSO aims to reduce the edges within a given network by reducing the smallest edges within the network to zero (Beard et al., 2016; Epskamp et al., 2012), this creates a more parsimonious network. The Fruchterman and Reingold algorithm via the R-package *qgraph* was used to visually depict each of the networks estimated (Epskamp et al., 2012; Fruchterman & Reingold, 1991). This layout aids visual interpretation of the network structure by positioning the most strongly correlated nodes together and by placing the most central nodes towards the centre of the network (Epskamp et al., 2012). The qgraph package also aids how the nature of edges are visually interpreted, edges are coloured either red (negative relationship) or blue (positive relationship). Edge thickness depicts the strength of connection i.e. thicker lines represent stronger connections between nodes (Epskamp et al., 2012).

Network Centrality

Centrality indicates the importance of each node within a given network. In the context of the current study expected influence (EI) was calculated (Borsboom & Cramer, 2013; Robinaugh et al., 2016). EI refers to a given nodes/symptoms influence with its neighboring symptoms/nodes (Robinaugh et al., 2016). This metric addresses issues around the more traditionally used centrality metric of 'node strength' as EI is calculated by summing the raw edge weights (+ and -), as opposed to node strength which calculates node centrality based on the absolute value of a given edge. Previous research has suggested that EI may be a more reliable indicator of centrality in the case where a given network has many negative edges (Robinaugh et al., 2016). In the present study, we estimated expected influence using the R package *qgraph* (Epskamp et al., 2012).

Modularity: Investigating Clusters of Symptoms

Clustering of symptoms within each of the estimated networks was explored using the 'Walktrap' community detection algorithm' (Pons & Latapy, 2005), available via the Exploratory Graph Analysis (EGAnet) package (Golino & Epskamp, 2017). However as 'Walktrap' is likely to find clusters of nodes even within a random network structure, it was also necessary to calculate the modularity index Q (Newman & Girvan, 2004). Q is calculated to determine how well-defined a given clustering structure is within a network (McElroy & Patalay, 2019). Q values closer to 0.3 reflect weakly defined communities, and values approx. 0.7 reflect strong community structures (Newman & Girvan, 2004).

Network Stability

The R package *'bootnet'* was used to investigate the accuracy and stability of each network estimated (Epskamp et al., 2018). Network stability estimation is a relatively new tool, it has not yet been refined to jointly estimated networks. Therefore, the stability of each network estimated in this study was investigated individually. Network stability was estimated in three ways; (1) bootstrapping 95% confidence intervals (CI) around edge weights, (2) estimating the correlation-stability co-efficient for centrality indices (values below 0.25 imply inadequate stability and values over 0.5 imply strong stability), (3) computing an edge-weights difference test for each network estimated (see Epskamp et al., 2018).

Latent Profile Analysis (LPA)

Latent profile analysis (LPA) is a mixture modelling technique used to identify homogenous groups/classes from continuous data (Weiss et al., 2018). LPA was used to identify whether different groups/classes of adolescents who varied in their ability to understand and regulate their emotions existed and what the nature of these classes/groups was.

A series of LPAs was estimated to identify the fewest latent emotional dysregulation profiles/classes. Seven models were specified and tested (a 2-class through to an 8-class solution) using MPLUS v7.3 (Muthén & Muthén, 2008). The models were estimated using robust maximum likelihood (Yuan & Bentler, 2000). To avoid solutions based on local maxima, 100 random sets of starting values were used. Several statistical model fit indices were used to identify the optimal number of latent classes. Specifically, by using three information theory-based fit statistics: the Akaike information criterion (AIC) (Akaike, 1987), the Bayesian information criterion (BIC) (Schwarz, 1978) and sample size-adjusted Bayesian information criterion (ssa-BIC; Sclove, 1987). The model that produced the lowest values was judged to be the best fitting model. The Lo-Mendell-Rubin (Lo et al., 2001) adjusted likelihood ratio test (LRT) was also used to compare models with increasing numbers of latent classes. When a non-significant value ($p > 0.05$) occurred, this indicated that the solution with one less class should be accepted.

Network Comparison Test

The primary aim of this study was to use NA to examine the anxiety-depression symptom network structures of adolescents with varying degrees of ER ability. This was achieved by partitioning the data into three sub data sets based on class membership derived from LPA and estimating the networks for each. These three networks based on ER ability (high, intermediate and low) were compared using a 'Network Comparison Test' (NCT; van Borkulo et al., 2017). NCT allows for the comparison of specific edges across networks, and tests invariance in overall connectivity (i.e. global strength) and structure using non-parametric permutation tests (see van Borkulo et al., 2017).

Results

Descriptive statistics for all PHQ-9 times and GAD-7 items, along with item labels are displayed in Table OS-1 (online supplementary).

Estimating a Psychological Network of Anxiety and Depression Symptomology in a School Based Adolescent Sample

Figure 1 depicts the network structure of depression and anxiety items among the entire sample, estimated using the GGM. A description of the node labels can be seen in Fig. 1. Out of a possible 120 edges (16*15/2), 79 (65.8%) were above zero. Generally positive edges were more commonly occurring and stronger than negative edges. The edge weights ranged between −.16 to 0.53, with positive edges being more common occurring than negative edges. The strongest edges identified in were between *'control worry'* and *'worrying often'* (0.53), *'nervous'* and *'control worry'* (0.34), *'sleep problems'* and *'tiredness'* (0.33), *'psychomotor retardation'* and *'restlessness'* (0.32), *'hopelessness'* and *'risk'* (0.31) and *'trouble relaxing'* and *'restlessness'* (0.30). The remaining nodes were weakly associated (< 0.30). Of the 6 strongest edges, only one edge linked depression and anxiety symptoms, between *'psychomotor retardation'* and *'restlessness'*. Moreover, connections between symptoms within each construct were stronger than the connections between constructs. The edge weights bootstrap (Fig. OS-2) showed that the 95% confidence intervals for many of the edges were overlapping. Furthermore, there were few significant differences between the strongest edges; this therefore indicates that the ranking of edge weights should be interpreted with care (Fig. OS-3).

Centrality Estimates

Standardised expected influence centrality estimates for the overall network structure is presented in Fig. 2. Stability analyses indicated a stable order of expected influence with a CS coefficient of 0.6 (Fig. OS-4). The symptom with the highest EI was *'control worry'* (2.04), followed by *'hopelessness'* (1.10).

Finally, the presence of meaningful clusters of symptoms within the network was explored using the Walktrap community detection algorithm (see Fig. OS-1). Based on the Walktrap analysis, a community structure of three clusters was detected. However, the Q-index of modularity value was below acceptable ($Q = 0.29$), indicating that the clusters were most likely random in nature. Q values lower than 0.3 suggest random clustering (Newman & Girvan, 2004).

Identification and Characteristics of Latent Classes

The fit indices for the LPA are displayed in Table 1. As aforementioned, a 2-class to an 8-class solution were specified and

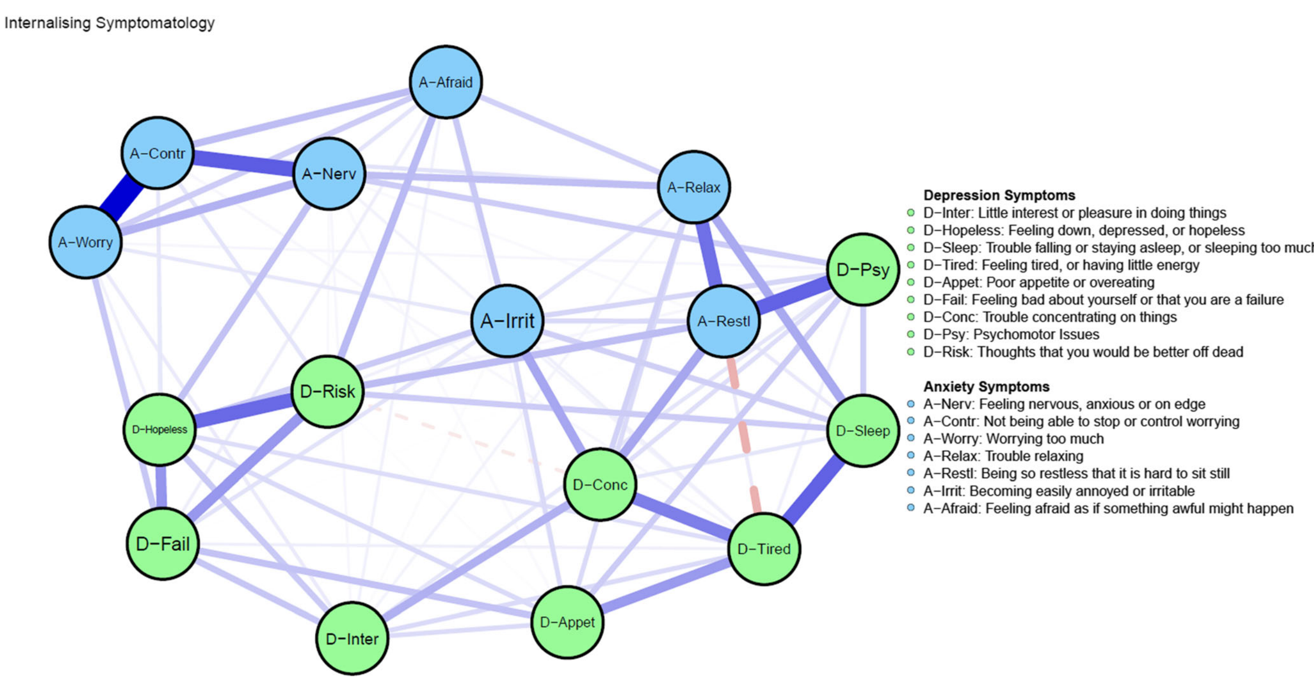


Fig. 1 Overall Network Structure of Anxiety and Depression based Symptomatology (full sample)

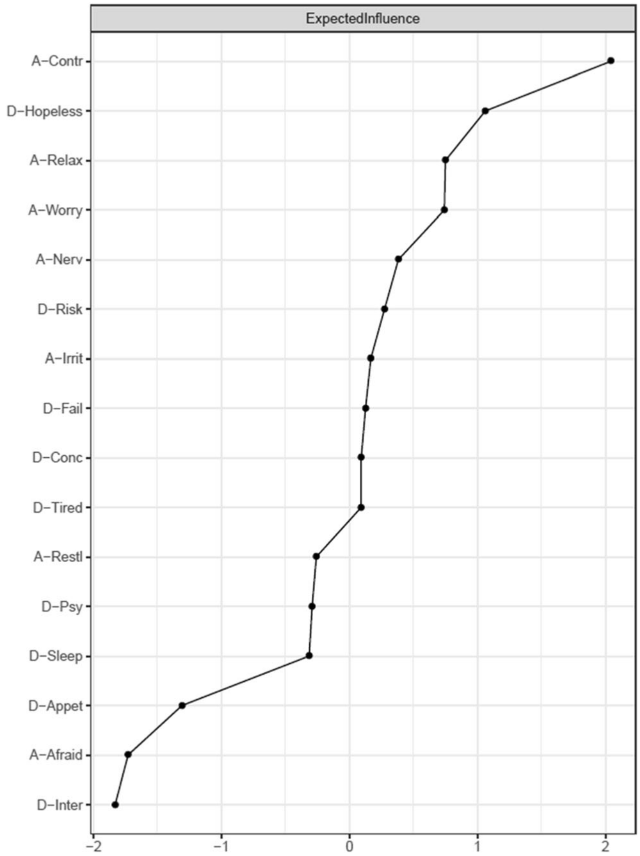


Fig. 2 Centrality Estimates for the Overall Network Structure. *Note: Centrality values (presented as Z-scores) for full sample ($N = 615$)

tested. The AIC, BIC and ssaBIC continued to decrease from a 2-class solution through to an 8-class solution. Despite this, the LRT value became non-significant at the 4-class solution. This suggested that the model with one fewer class should therefore be accepted; in this case this was the 3-class solution. Furthermore, the AIC, BIC and ssBIC values for the 3-class solution were lower than the corresponding values from the 2-class solution. Moreover, the AIC, BIC and ssBIC values for the subsequent class solutions (4-class to 8-class solution) indicated "flattening" i.e. that the subsequent decreases were smaller than those observed between the 2 and 3-class solutions (Weiss et al., 2018). The entropy value for the 3-class solution was 0.96, indicating acceptable classification of participants in this particular model. Average latent class probabilities for most likely class membership were 0.98 for class 1, 0.97 for class 2 and 0.94 for class 3, indicating good class discrimination. The 3-class solution was accepted as the most parsimonious.

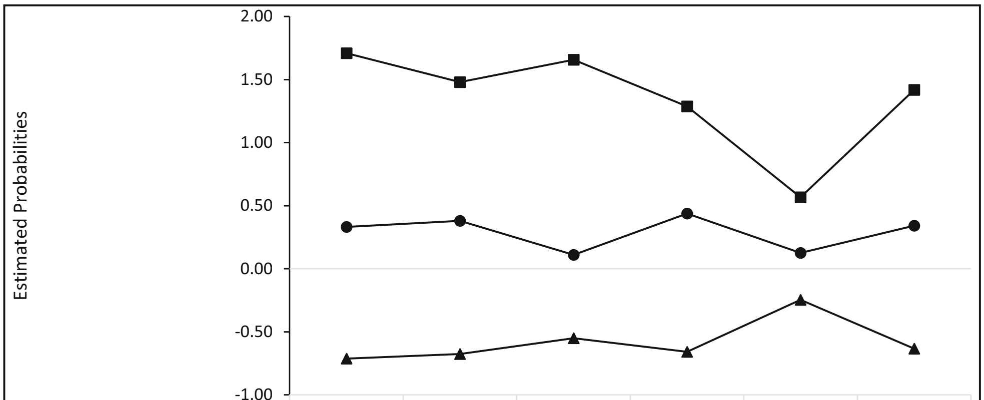
The three profiles demonstrated varying degrees of severity in emotion dysregulation (see Fig. 3). Class 1 contained 15% ($N = 92$) of the sample and was characterised by having the greatest difficulties in regulating their emotions, overall demonstrating the highest scores across all six dimensions of the DERS-SF. This class was labelled the *'low ER ability'* class. In comparison to the other two classes, class 1, when experiencing intense negative emotions, had the greatest difficulty engaging in goal directed behaviour, had limited access to strategies to help to regulate their emotions, were unable to accept their distress, had no clarity on which emotions they were experiencing and often acted on impulse. This group, although overall scoring the highest across all DER-SF scales, had the lowest score for the 'lack of emotional awareness' subscale compared with the other five subscales.

Class 2 contained 51.2% ($N = 315$) of the sample and was characterised by an above average ability to regulate their emotions well, compared to classes 1 and 3. Of the three classes, class 2, when experiencing intense negative emotions, were the group of adolescents most capable of engaging in goal directed behaviour, having good access to strategies to regulate their emotions, accepting that they were distressed, being clear on which emotions they were experiencing and not acting on impulse. This group demonstrated a greater awareness of their own emotions but had the lowest score on this subscale than the other five subscales. This class was labelled as the *'high ER ability'* class.

Finally, class 3 represented 33.8% ($N = 208$) of the sample, demonstrating relatively low scores across all six DERS-SF subscales. This class demonstrated relatively intermediate scores across all six DERS-SF subscales. This class is

Table 1 Fit Indices for Latent Profile Analysis of DERS-SF Subscales

Classes	Log-likelihood	AIC	BIC	ssaBIC	Entropy	LRT, *p*
2 Class	−4040.601	8119.201	8203.212	8142.891	0.924	1806.827*
3 Class	−3677.626	7407.252	7522.215	7439.670	0.915	710.151*
4 Class	−3523.348	7112.695	7258.609	7153.840	0.905	301.842
5 Class	−3438.410	6956.820	7133.685	7006.692	0.921	166.177*
6 Class	−3380.040	6854.080	7061.896	6912.680	0.878	114.200*
7 Class	−3327.285	6762.569	7001.337	6829.897	0.884	103.223
8 Class	−3284.363	6690.727	6960.446	6766.782	0.886	83.972



	Strategies	Non-acceptance	Impulse Control	Goals	Awareness	Clarity
Low ER Ability (15%)	1.71	1.48	1.66	1.29	0.57	1.42
High ER Ability (51.2%)	-0.71	-0.68	-0.55	-0.66	-0.25	-0.63
Intermediate ER Ability (33.8%)	0.33	0.38	0.11	0.44	0.13	0.34

Fig. 3 Profile Plot for 3-Class Latent Profile Analysis of DERS-SF Subscales

characterised by an ability to adequately regulate their emotions, showing no greater than average difficulty across the six DERS-SF subscales. Class 3 was labelled as the *'intermediate ER ability'* class. Overall, there was little variation in the probability estimates for the *'lack of awareness'* subscale between classes, indicating that for this sample, lack of emotional awareness was not a prominent or distinguishing feature of emotional dysregulation.

Investigating the Impact of Emotion Regulation on a Psychological Network of Anxiety and Depression in Adolescence

An anxiety-depression network for the 'High ER' group could not be reliably estimated due to a lack of variance within this particular group. This subsequently led to the production of a 'non positive definite matrix' which interfered with the

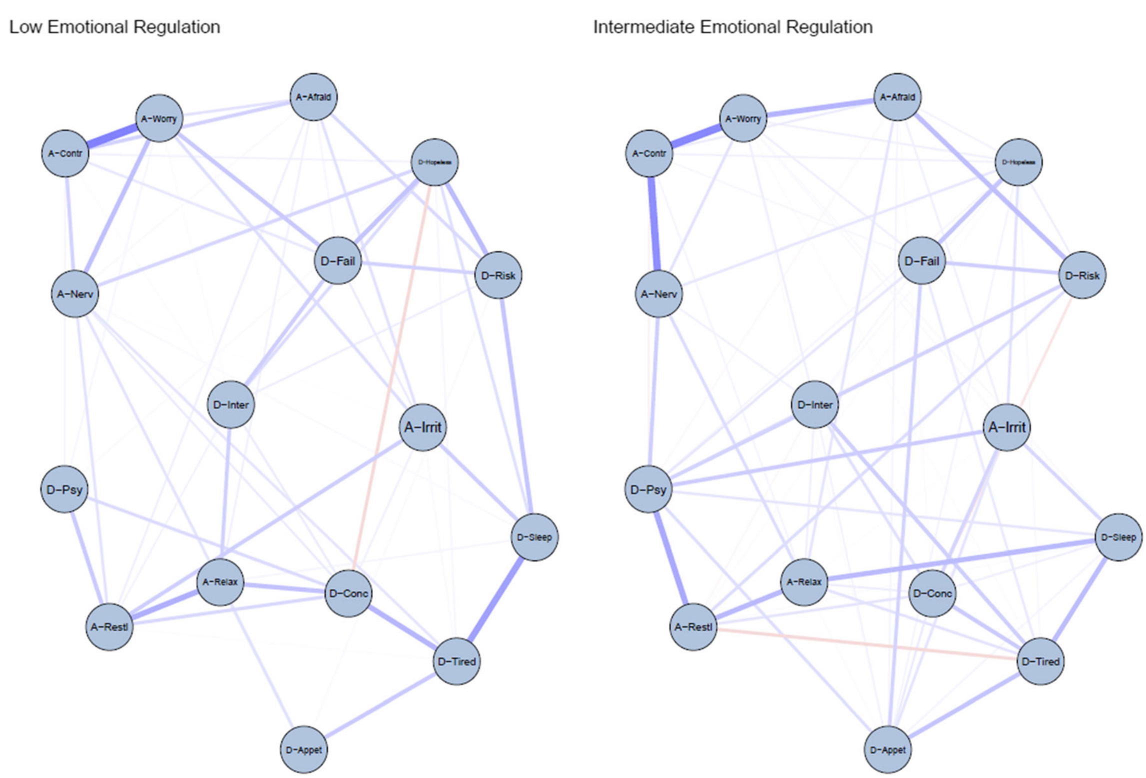


Fig. 4 Network Structure of Anxiety and Depression items based on Emotional Regulation Ability

reliable estimation of the network (see Epskamp et al., 2017). Subsequent analyses therefore were based on the anxiety-depression networks estimated for the 'low ER' and 'intermediate ER' ability groups only.

Network Estimation

Networks were estimated separately for both ER ability classes (low ER and intermediate ER ability; see supplementary S5–6). For ease of visual comparison, both ER ability networks were restricted to a consistent 'average layout' and are presented in Fig. 4. A description of the node labels and item descriptions can be seen in Table OS-1.

Firstly, in terms of the 'low ER ability' network, of a possible 120 edges (16*15/2), 58 (48.3%) were above zero. Generally positive edges were more commonly occurring and stronger than negative edges. The edge weights ranged between −0.14 to 0.49, with positive edges being more common occurring than negative edges. The strongest edges identified in were between *'control worry'* and *'worrying often'* (0.49), *'sleep problems'* and *'tiredness'* (0.37), *'trouble relaxing'* and *'restlessness'* (0.31), *'sleep problems' and 'concentration'* (0.28), *'hopelessness'* and *'risk'* (0.26) and *'nervous'* and *'worrying often'* (0.24). Of the strongest edges identified, none linked depression and anxiety symptoms. Therefore, connections between symptoms within each construct were stronger than the connections between constructs. The edge weights bootstrap (Fig. OS-9) showed that the 95% confidence intervals for many of the edges were overlapping. Furthermore, there were few significant differences between the strongest edges; this therefore indicates that the ranking of edge weights should be interpreted with care (Fig. OS-10).

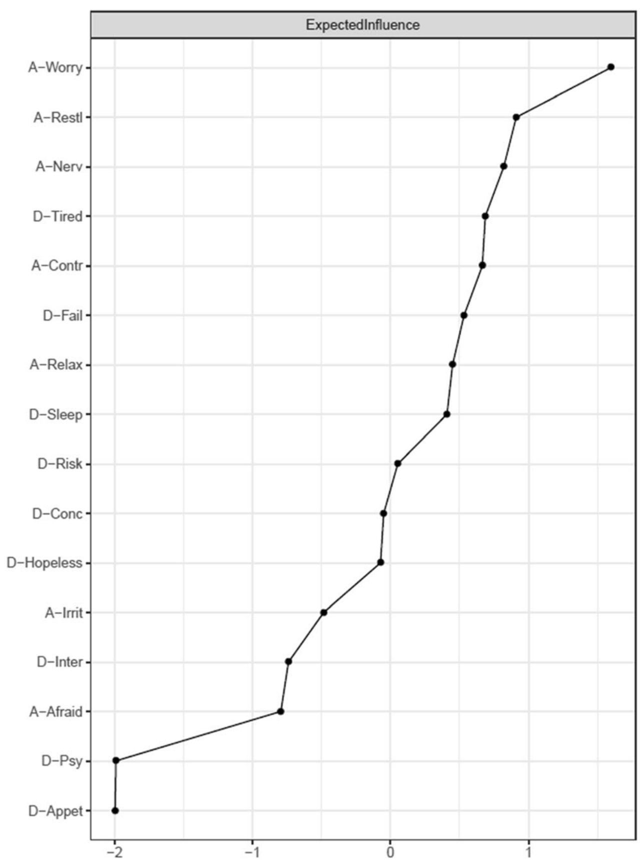


Fig. 5 Centrality Values (presented as Z-scores) for the Low Emotional Regulation Group. *Note: Centrality values (presented as Z-scores) for full sample (N = 615)

Looking towards the 'intermediate ER ability' network, of a possible 120 edges (16*15/2), 73 (60.83%) were non-zero. The strongest edges identified in the network were between *'control worry'* and *'worrying often'* (0.47), *'nervous'* and *'control worry'* (0.44), *'psychomotor retardation'* and '*restlessness' (0.33), 'worrying often'* and *'feeling afraid'* (0.29), *'trouble relaxing'* and '*restlessness'* (0.27) and *'sleep problems'* and *'trouble relaxing'* (0.26). Of the strongest edges identified, two linked depression and anxiety symptoms, *'psychomotor retardation'* and '*restlessness',* and also, *'sleep problems'* and *'trouble relaxing'*. Overall, connections between symptoms within each construct were stronger than the connections between constructs. The edge weights bootstrap (Fig. OS-12) showed that the 95% confidence intervals for many of the edges were overlapping. Furthermore, there were few significant differences between the strongest edges; this therefore indicates that the ranking of edge weights should be interpreted with care (Fig. OS-13). The most consistently strong edge across both estimated ER ability networks was between anxiety symptoms *'control worrying'* and *'worrying often'. This connection was stronger in the low ER network.*

Centrality Estimates

Standardised expected influence (EI) centrality estimates for both the low ER and intermediate ER network structures are presented in Figs. 5 and 6, respectively. Firstly, in the context of the intermediate ER network the symptoms with the highest EI centrality were, *'psychomotor retardation/agitation'* (2.10), *'worrying often'* (1.11), *'trouble relaxing'* (0.99) and *'control worrying'* (0.95). *'Anhedonia'* and *'risk'* had the lowest EI. In relation to the 'low ER' network, the symptom with the highest EI was *'worrying often'* (1.60), followed by 'restlessness' (0.91) and 'feeling nervous' (0.82). The symptoms with the lowest expected influence in the 'low ER' network, were *'psychomotor retardation'*, followed by *'appetite/weight loss'*. Stability analyses revealed a CS coefficient of 0.44 for the intermediate ER network (Fig. 14-OS) and 0.21 for the low ER network (Fig. 11-OS). This indicates the EI centrality estimates should be interpreted with caution, particularly in relation to the low ER network.

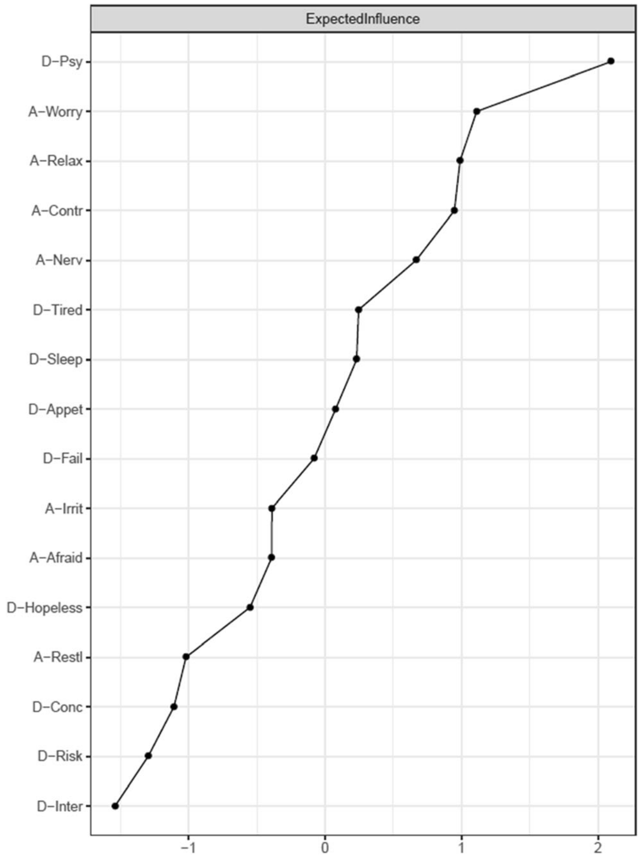


Fig. 6 Centrality Values (presented as Z-scores) for the Intermediate Emotional Regulation Group. *Note: Centrality values (presented as Z-scores) for full sample (N = 615)

Community Detection

The presence of meaningful clusters of symptoms within both ER ability networks was explored using the Walktrap community detection algorithm. This was important to explore as it was hypothesised that in the context of poor ER ability, symptoms of anxiety and depression may have reflected what is typically recognised in clinical practice and diagnoses as anxiety and depression i.e. grouped into meaningful within disorder clusters. Additionally as both ER ability groups contained unequal samples, a random selection of 92 observations from the intermediate groups was computed in R in order to create two equal samples to match the 92 observations within the 'low ER ability' group. The intermediate ER network was then re-estimated and the Walktrap community detection algorithm carried out again to explore meaningful clustering when all samples for each network were of equal size (see Fig. OS-8).

A community structure of three clusters of nodes was detected for the 'intermediate ER ability' network. Again, this was also the case for the *'matched sample intermediate ER ability'* network. The Q-index of modularity value was below acceptable ($Q = 0.26$), indicating that the clusters were most likely random in nature. This was also the case for the *'matched sample intermediate ER ability'* network, were the modularity value was 0.31. Additionally, a community structure of four clusters of nodes was detected for the 'low ER ability' network. However, the Q-index of modularity value was not acceptable ($Q = 0.22$), indicating that the clusters were most likely random in nature.

Network Comparison Tests

Network comparison permutation tests were used to empirically compare whether both` ER ability networks significantly differed from one another. The results of the NCT found no significant difference in global strength between the 'low ER' and the 'intermediate ER' ability network. As a robustness check a random selection of 92 observations from the intermediate group was computed in R to create an equal sample to match the 92 observations within the 'low ER ability' group. The intermediate ER network was then re-estimated and the NCT permutation tests were carried out again. In the case of the matched sample sizes the results of the NCT permutation tests remained the same.

Discussion

This exploratory study had two aims (1) to examine the general symptom structure of depression and anxiety based symptoms among school age adolescents within the general population and explore the extent to which depression and anxiety are distinct constructs within this sample, and, (2) to examine changes in anxiety-depression symptom connectivity in the context of ER.

The General Symptom Structure of Anxiety and Depression Symptoms among Female Adolescents

Regarding the overall sample network structure, the symptom with the highest expected influence centrality, and thus having the most influence on its neighboring symptoms was the anxiety symptom *'control worrying'*. This was followed by the depression symptom *'hopelessness'*. This tentatively suggests the presence of these symptoms may increase the likelihood that more serious symptoms in the network may be activated, indicating these symptoms may play a role in the onset and maintenance of anxiety and depression based symptoms in adolescence. This is supported by previous empirical research, where symptoms of sadness and worry were found to be highly central within a general population adolescent network of anxiety/depression (McElroy et al., 2018). McElroy et al. (2018) suggest that these symptoms like 'low mood' and 'worry' can be seen to represent negative affect states, *"which may be thought of as most closely mirroring the underlying* *neurobiological systems subserving negative valence or the core appraisals within a cognitive-behavioural framework linked to perceived threat or loss"*(p. 17, McElroy et al., 2018). This is particularly relevant largely due to a wealth of research identifying adolescence as the most crucial developmental stage for affective development and the links between negative affect and psychopathology (McLaughlin et al., 2011). Specifically, many adolescents will face challenging circumstances e.g. increasing independent interaction with peers, romantic relationships, exposure to substance abuse and other risky behaviours, that they must circumnavigate and manage intense emotions (McLaughlin et al., 2011). These highly central symptoms are particularly relevant and applicable to several transdiagnostic therapeutic approaches and consistent with prior empirical research in the context of adolescence (McElroy et al., 2018).

However, it is imperative that the above findings are interpreted within the context of the sample being studied (i.e. a female only sample from the general population). The item with the highest expected influence centrality, and therefore having the greatest influence on its neighboring symptoms, was '*not being able to stop or control worrying*' may be reflective of the context in which the study was conducted. Tentative explanations may be that adolescent's in today's society are living in an increasing digital world, where daily usage of multiple social media platforms is highly prevalent (Primack et al., 2017), and may perpetuate worry states. For example, increased self-consciousness, peer comparison, image scrutiny, peer exclusion, and cyber-bullying to name a few. This has subsequently been linked to an inability to sustain attention and exacerbate anxiety symptoms such as worry and depressive symptoms such as sleep troubles, concentration issues and low mood in adolescence (Primack et al., 2017). Previous research also suggests an increase in caffeine consumption in today's youth, coupled with exam pressures, which may also offer further explanation (Owens and Adolescent Sleep Working Group, 2014). Moreover, one of the core DSM-5 symptoms required for a diagnosis of MDD is *'anhedonia',* had the lowest expected influence within the current sample. However, it is likely that this finding is reflective of the context in which this data has been gathered i.e. a non-clinical female sample, where key features of MDD would not be expected to be prominently evident. Additionally, research has shown males are more likely to exhibit higher rates of anhedonia than females, which may explain why it was not a more integral feature within the network structure (Doti et al., 2012).

Overall, the network was a highly interconnected network, with no evidence of distinct within symptom clustering evident in relation to the distinct domains of GAD and MDD (Fig. 1). Two recently published studies using non-clinical (McElroy et al., 2018) and clinical adolescent samples (McElroy & Patalay, 2019) lend support to this finding. Specifically, McElroy et al. (2018), utilising a large non-clinical adolescent sample, found that there was little to separate the domains of depression and anxiety in adolescence, complementing the findings of the current study. Moreover, previous adult general population studies (with same psychometric measures as the current study), have also yielded similar results (Cramer et al., 2010).

While GAD and MDD symptoms clustered together within this network structure, closer examination of the edge weights revealed that the connections between symptoms within each disorder were stronger than the connections between disorders. This is also in line with previous similar studies (Beard et al., 2016; Jones et al., 2018). Of the strongest edges, only one edge linked depression and anxiety symptoms, with *'psychomotor retardation'* and *'restlessness'* serving as bridging nodes across domains. The role of *'restlessness'* as a bridging node between anxiety and depressive symptoms has been supported by previous similar research (Beard et al., 2016). Overall, the edges between *'worrying often'* and *'control worry'* were stronger than all other edges in the network, a finding also in line with previous similar studies (Beard et al., 2016).

Each of these findings (1) the lack of evidence for distinct clusters reflecting the distinct domains of GAD and MDD and, (2) the connections between symptoms within each disorder were stronger than the connections between disorders, appear to paint a contradictory picture of anxiety and depression symptom distinctiveness and symptom connectivity among adolescents. However, it is important to review Fig. 1 again, which depicts depression and anxiety symptom connectivity based in a sample without *context*; the context being a cross sectional sample of adolescent females in the general population. This represents a key challenge when interpreting and disseminating such networks which are generated using cross sectional general population data. In the case of the current study, without context, we are faced with several important considerations about how we interpret such networks. Specifically (1) does this network reveal the genesis of anxiety and depression symptom connectivity or (2) does this network reveal already established connectivity of anxiety and depression symptoms. These are challenging conceptual and methodological hypotheses that cannot be answered by examining the general network structure of symptomology solely without context or prospective data. However, we argue that this was first necessary to explore the complex interplay between these symptoms across the entire sample. Fried et al. (2017) state that an important step to investigating the complex interplay between symptom associations is to first identify associations that appear consistently across many people. This in turn allows for the testing of novel hypotheses and the exploration of what mechanisms possibly underly symptom connectivity (Fried et al., 2017). It was therefore the primary goal of the current study to impose *context* by examining depression and anxiety symptom connectivity among adolescent females in the *context* of ER.

The Impact Emotion Regulation Ability on the Network Structure of Anxiety and Depression Symptomatology in Adolescence

The current study aimed to estimate and compare networks of depression and anxiety symptoms at varying levels of ER within a non-clinical adolescent sample. Given the well-established evidence base demonstrating the transdiagnostic quality of ER in adolescence, it was hypothesised that ER may be a plausible mechanism for explaining the context in which a network of anxiety and depression symptoms might begin to connect, perpetuate, and ultimately diverge. At the lowest levels of ER, it was hypothesised that this anxiety-depression network would be most reflective of what is recognised clinically as depression and anxiety, demonstrating greater overall global connectivity and clear evidence of within disorder clustering (i.e. separation of symptoms into their relevant disorder) in comparison to both the intermediate and high ER anxiety-depression networks. However, this path was met with methodological challenges, which meant that an anxiety-depression network for the 'High ER' group could not be reliably estimated, due to a non-positive definite matrix, likely the result of a lack of statistical power or variance. Terluin et al. (2016) highlight that issues surrounding variance are particularly prevalent when studying psychological networks within healthy populations or samples (see Terluin et al., 2016). Therefore, the dissemination of findings will focus on the anxiety-depression networks estimated for the 'low ER' and 'intermediate ER' ability groups only.

In the context of both the *low* ER network and *intermediate* ER network structures, the current study found no evidence of distinct within symptom clustering in relation to GAD and MDD. Therefore, it appears even in the context of low ER ability (i.e. emotion dysregulation), clear separation of symptoms into their relevant construct is not evident. This therefore highlights the complexity of internalising symptomology in adolescence (McElroy et al., 2018), as the current findings may suggest that even in the case of a network structure based on individuals with low ER ability, that there is still little that separates the constructs of anxiety and depression in adolescence. The authors acknowledge this study utilised data from a non-clinical sample, however previous similar general population and clinical adolescent based studies using network analytic techniques have yielded similar results (McElroy et al., 2018; McElroy & Patalay, 2019).

Regarding symptom importance, the GAD symptom *'worrying often'* had the highest expected influence followed closely by GAD symptoms, *'restlessness'* and *'feeling nervous'* for the 'low ER ability' network. This tentatively suggests that the presence of these symptoms may increase the likelihood that more serious symptoms in the network may be activated. This makes intuitive sense in the context of emotion dysregulation, as aforementioned, symptoms such as intense worry or nervousness can be representing 'negative affect states' (McElroy et al., 2018). Therefore, one possible interpretation (in the context of this emotionally dysregulated group) is that these adolescents are unable to implement adaptive ER regulation strategies to manage the distress experienced by this intense worry (Klemanski et al., 2017; McLaughlin et al., 2011; Schäfer et al., 2017). The findings yielded from the LPA demonstrated that this group of adolescents had the greatest difficulty engaging in goal directed behaviour, have limited access to strategies to help to regulate their emotions, are unable to accept their distress, have no clarity on which emotions they are experiencing and often act on impulse. Therefore, it stands to reason when experiencing intense worry or nervousness, this group of adolescents are more likely to implement maladaptive ER strategies e.g. avoidance or rumination (Schäfer et al., 2017). In theory, when a person utilises maladaptive ER strategies, this could in turn lead to other internalising symptoms becoming 'activated' e.g. sleep or appetite problems and overtime more serious symptoms such as low mood, anhedonia, hopelessness, suicidal ideation; therefore allowing for the dynamic interactions and mutual reinforcement between the other internalising symptoms in the network. Therefore these highly central symptoms are particularly relevant and applicable to a number of transdiagnostic therapeutic approaches where ER is a core component of case conceptualisation and treatment (Neacsiu et al., 2014), and is also consistent with prior empirical research in the context of adolescence (McElroy et al., 2018). However, given the low stability of the low ER network, these findings can only be considered exploratory, and therefore should be interpreted with caution.

Additionally, it was expected that core symptoms required for a diagnosis of MDD would be highly influential within the low ER network, however this was not the case. Interestingly MDD symptom *'anhedonia'* which is one of the essential criteria necessary for a diagnosis of MDD according to DSM-5 criteria (American Psychiatric Association, 2013), had among the lowest expected influence. This may be reflective of the sample. Previous research has shown males are more likely to exhibit higher rates of anhedonia than females, whereas females are more likely to experience MDD symptoms such as sleep, appetite, and concentration problems as well as fatigue, which may shed light on the above findings (Fried et al., 2014). As expected, in the context of the intermediate ER ability network, the MDD symptoms which pertain to *'anhedonia'* and *'hopelessness,* which are essential for a diagnosis of MDD according to DSM-5, had the lowest expected influence. *'Risk'* was also low on expected influence, therefore having little influence over other symptoms within the network. This could tentatively suggest that an ability to effectively manage and regulate one's emotions prevents these symptoms from being able to manifest.

Finally, network comparison permutation tests were used to empirically compare whether both ER ability networks significantly differed from one another. The findings indicated that there were no significant differences in the overall connectivity of the ER ability networks, even in the case of the matched sample sizes. While this was a surprising finding, this may be reflection of the limitations of the data used to test our hypothesis. Specifically, given the small sample size, the current study may not be adequately powered to detect meaningful differences between these networks. At the time of writing, the authors were not able to source an available large scale secondary data set which adequately captured ER ability among the age range of interest. The authors intention was to use this exploratory study as a first step to explore ER as a plausible mechanism for explaining the context in which a network of anxiety and depression symptoms might begin to connect, perpetuate and ultimately diverge. More specifically to propose a conceptual framework to explain symptom connectivity among networks of internalising symptoms in adolescent samples. Therefore, the authors stress the value of the conceptual framework put forward in the current study, alongside the study design but assert caution in the interpretation of the data given the low stability of the low ER network. Consequently, it is imperative that the hypotheses proposed in the current study are further examined using more adequately powered data. Further, ER should be considered a fruitful avenue of exploration in future NA studies examining internalising symptomatology in adolescence, given the existing empirical evidence base.

Limitations & Future Research Recommendations

The results of this study should be interpreted within the context of the following limitations. The main limitation of this study lies within its generalisability. This is a small-scale study which focused on two N.I all-female post-primary schools, meaning it is not possible to generalise the findings to adolescent males, cross culturally or to the wider population. Further, females have been consistently shown to exhibit greater depression/anxiety based symptomatology, alongside research which suggests variability in ER exists between males and females (Polanczyk et al., 2015; Silk et al., 2003; Zimmermann & Iwanski, 2014). Therefore, the findings need to be interpreted within that context. It would therefore be useful for future studies to examine whether similar findings are evident in male adolescents also.

Secondly, the data collected as part of this study was cross sectional in nature, therefore assumptions regarding causality cannot be made. Specifically, regarding the temporal ordering of ER ability and internalising psychopathology. Although a network approach is a natural fit for examining cross sectional data in more depth due to the emphasis on the dynamic interaction between symptoms, experimental, longitudinal or time series data would still be greatly needed in future replication studies. Therefore, it is vital to consider the type of data necessary in order to more adequately test our hypothesis. In particular, the low stability of the ER networks (0.21 and 0.44) must be noted and caution regarding the interpretation of the data should be asserted. Stability values should be at least over 0.25, and ideally over 0.5. This therefore suggests that the study of the variation of internalising symptoms and ER ability among adolescents may benefit from larger sample sizes and/or more novel types of data (e.g. individualistic time series data; Kirtley et al., 2020). Given these data related limitations, it is imperative the hypotheses proposed in the current study are further examined using more adequately powered data.

Moreover, given the cross-sectional nature and modest sample size, symptom structure over development could not be explored. Future studies could also seek to replicate the findings of the current study using longitudinal data to explore this. However, McElroy et al. (2018) explored the network structure of anxiety-depression across five different time points in a general population sample of adolescents, finding their interconnectivity, relations between symptoms and centrality remained stable over all time points. Nevertheless, it is not yet clear whether ER ability would remain relatively stable longitudinally in the context of NA. This is important to consider in future research given that previous studies have demonstrated specific developmental changes in the use of emotion regulation strategies. Specifically, Zimmermann and Iwanski (2014) examined ER strategy use across the ages 11 to 50. The findings suggested that age specific increases and decreases in the use of many ER strategies occurs throughout development. The results indicated that as participants aged, the use of adaptive ER strategies increased. Further, adolescence was demonstrated to be the developmental stage with the lowest capacity for ER (Zimmermann & Iwanski, 2014).

Thirdly, as this study pertained to school-based data, it is not yet clear whether the results would differ in adolescence to clinical data, where it would be expected that levels of emotional dysregulation would be high. Further given the limits regarding the information available in the data set used in this study, current or prior mental health diagnosis or other factors such as experience of adverse childhood experiences could not be controlled for. Such factors may play an important role in the ability to develop a healthy emotional regulation style.

Additionally, given that network analysis itself is a relatively new analytical tool, it carries its own specific limitations. Namely, the appropriate statistical tests required to determine reliability are continually being refined (Levinson et al., 2017). Therefore, it is vital to consider the subjective nature of network interpretation (Murphy et al., 2017). All three networks examined in this study are exploratory, much further research is required. Most importantly, it is vital to be aware of the challenges of conducting analysis by selecting sub populations and comparing the differences, especially in terms of network modelling. A recent paper by Ron and colleagues highlighted this issue, known as Berkson's bias (See de Ron et al., 2019, preprint). These issues are also further discussed in a recent preprint by Haslbeck and colleagues (Haslbeck et al., 2020). Therefore it is important not to over interpret the findings of the current study as aforementioned our analytic plan was met with methodological and statistical challenges (e.g. small sample size and lack of variance) that have been highlighted to coincide with estimating networks by selecting sub populations and comparing the results (Terluin et al., 2016), as well as the low stability of the low ER network. While the authors acknowledge that current approaches to overcome such biases in correlational research are still under development (de Ron et al., 2019), some solutions have been suggested (Haslbeck et al., 2020). Therefore, in line with these suggestions, moving forward studies seeking to build upon the hypotheses generated in this study should consider the use of moderated network models (Haslbeck et al., 2019). This approach allows for the exploration of the extent to which certain variables such as emotion regulation moderate the interactions between symptoms within the network. This approach may also address network stability issues as it affords exploration of such hypotheses utilising the power of the full sample.

Despite this, the current study has a number of strengths. Firstly, a combination of sophisticated analytic techniques were employed to explore the role of ER in relation to internalising symptoms in an adolescent sample. Secondly, this study (to the authors knowledge) was the first to attempt to compare the network structure of anxiety and depression symptomology based on variations in ER ability and is therefore novel in nature and generates hypotheses for future research.

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Code Availability All R code is provided in the online supplementary materials.

Author Contributions All authors contributed to the study conception and design. EMG gathered the data associated with the paper, conducted the analysis and wrote the first draft of the paper, in close collaboration with her supervisors KK and JM. JM and EM assisted the EMG with the analysis and interpretation of findings. All authors contributed to the writing revised versions of the manuscript and reviewed and approved its final version.

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Data Availability The participants did not give assent (and their parents did not give consent) for their data to be made publicly available. Further it is possible for certain individuals to be identified from the data set. However all R code is provided in the online supplementary materials. Derived data supporting the findings of this study will be made available from the corresponding author on reasonable request.

Declarations

Ethical Approval Ethical approval was granted by Ulster University's Research Ethics Committee (REC/16/0007).

Consent to Participate All participants involved in the current study provided informed consent. Further as the study involved the participation of adolescents 18 or younger, parent assent was also provided for all participants involved.

Consent to Publish The authors affirm that all participants provided informed consent/assent for the findings to be published.

Conflict of Interest No potential conflict of interest was reported by the authors.

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